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Keywords

adaptive performance, GMA, choking, goal theory, performance trajectory

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General Mental Ability and Goal Type as Antecedents of Recurrent Adaptive Task Performance

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Abstract

Even though considerable work has demonstrated a robust positive relationship between general mental ability (GMA) and task performance, recent work indicates that the expected relationship may not hold in the context of adaptive performance. By integrating the concept of choking, or performing worse than expected, with goal theory, the present work advances a theoretical framework aimed at furthering our understanding of how and when GMA is most likely to meaningfully impact performance. Drawing on this perspective, we propose that the relationship between GMA and adaptive performance is uniquely dependent on the type of goal individuals are striving to achieve. Additionally, we note that the nature of this relationship may evolve as people gain experience dealing with unexpected changes. Results of a discontinuous growth model fit to data obtained from a stock market exercise generally indicate that compared to performance goals, do-your-best and learning goals strengthen the relationship between GMA and adaptive performance. Further, we find that performance goals seem to effectively neutralize the GMA-adaptive performance relationship by benefiting those lower on GMA while simultaneously hindering those with higher levels. In contrast, the relationship is largely positive when either a do-your-best or a learning goal is being pursued, particularly after individuals are exposed to a second change.

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General Mental Ability and Goal Type as Antecedents of Recurrent Adaptive Task Performance

Research has consistently demonstrated that general mental ability (GMA), "the general efficacy of intellectual processes" (Ackerman, Beier, & Boyle, 2005, p. 32), is a strong predictor of task performance (Schmidt, Shaffer, & Oh, 2008). In fact, "cognitive ability is widely considered to be the single best predictor of learning and performance, especially on difficult and complex tasks" (Bell & Kozlowski, 2002, p. 497). However, as workplaces become more uncertain (Burke, Pierce, & Salas, 2006; Pulakos, Arad, Donovan, & Plamondon, 2000), traditional means of defining and evaluating employee performance may no longer be valid (Cortina & Luchman, 2013). This has led scholars to explore the extent to which GMA is still relevant for predicting performance as the criterion domain has continued to expand.

In particular, *adaptive performance*, or task-relevant behaviors exhibited in response to changes in the complexity of the task environment (Baard, Rens, & Kozlowski, 2014; Campbell, 1999; Dorsey, Cortina, & Luchman, 2010; Griffin, Neal, & Parker, 2007; Hesketh & Neal, 1999; Johnson, 2003; LePine, 2005; Pulakos et al., 2000), has been identified as a critical area of inquiry for scholars wishing to better understand and manage employee performance in contemporary organizations (Jundt, Shoss, & Huang, 2015; Pearlman & Barney, 2000). While early work in this domain generally found a positive relationship between GMA and adaptive performance (e.g., Allworth & Hesketh, 1999; LePine, Colquitt, & Erez, 2000; Pulakos et al., 2002), more contemporary investigations have cast those findings into doubt, with some recent work reporting a negative relationship (Lang & Bliese, 2009). We aim to further our theoretical understanding of this relationship by proposing and evaluating a critical boundary condition (Busse, Kach, & Wagner, 2017) to explain such seemingly incongruous findings.

To fulfill this aim, we draw on and extend Sian Beilock and her colleagues' work on choking, or "performing more poorly than expected given one's level of skill" (Beilock & Carr, 2001, p. 701). By integrating their work with goal theory, we develop a theoretical basis for understanding how and when contextual factors may systematically influence the GMA-adaptive

performance relationship. In so doing, we provide a means of understanding when we should (and should not) expect higher (lower) levels of GMA to lead to increased (decreased) adaptive performance. Building on LePine's (2005) assertion that goal attributes and GMA should jointly influence adaptive performance, we demonstrate the utility of our perspective by considering how different goal types affect the robustness of the GMA-adaptive performance relationship. Specifically, we propose that the increase in felt pressure to perform associated with performance goals (relative to do-your-best and learning goals) will disrupt the complex task-completion approaches preferred by those higher on GMA, diminishing their adaptive performance. In contrast, this incremental pressure to perform is likely to provide needed focus for those lower on GMA, enhancing their adaptive performance. Consistent with our theoretical rationale, we find that performance goals seem to diminish the effect of GMA while do-your-best and learning goals foster a generally positive relationship between GMA and adaptive performance.

By answering calls to jointly consider contextual and individual factors, the present study contributes much needed theoretical depth to our understanding of the relationship between GMA and adaptive performance (Jundt et al., 2015; Lang & Bliese, 2009). Extending Beilock and colleagues' (e.g., Beilock & Carr, 2001; Beilock & Carr, 2005; Beilock & DeCaro, 2007) choking framework beyond high-stakes academic (e.g., math) settings to more typical work contexts, we demonstrate its utility for understanding the antecedents of adaptive (and task) performance. We also add additional theoretical rigor to this perspective by integrating goal theory (Locke & Latham, 1990) to better delineate the role that goal type plays in choking. In so doing, we establish a coherent framework for understanding the nuanced relationship between GMA, goal type, and performance over time in dynamic contexts. By highlighting the importance of matching goal type with the attributes of the individual and the type of performance desired, our efforts also provide a meaningful extension to goal theory.

Theoretical Background and Hypothesis Development

The choking framework put forth by Beilock (2010) provides a comprehensive means of understanding *how* and *when* GMA facilitates performance. Consistent with other theoretical

frameworks describing how GMA¹ relates to performance (e.g., cognitive resource theory: Kanfer & Ackerman, 1989), the choking framework delineates three key mechanisms that generally enable individuals with higher GMA to outperform those with lower GMA: increased complexity of task-completion approaches employed, enhanced ability to differentially focus on a subset of stimuli, and elevated level of self-imposed performance expectations.

How GMA Can Facilitate Performance

First, GMA is associated with the ability to implement complex task-completion approaches (Beilock & Carr, 2005). Those with higher GMA have a larger endowment of cognitive resources available (Kanfer & Ackerman, 1989) and have a propensity to employ those additional resources in a manner described as ‘if you’ve got it, flaunt it’ (Beilock & Carr, 2005, p. 102). This results in the development and execution of more complex, explicit approaches to task completion. In contrast, those with lower GMA generally rely on simpler associative approaches incorporating heuristics and other efficiency-enhancing shortcuts to make the most of their limited capacity (Beilock & DeCaro, 2007). In the realm of completing classification tasks, these two approaches represent the difference between doing the mental math necessary to systematically work through the steps and arrive at the answer vs. relying on an educated guess based on high-level attributes of the problem (e.g., whether the numbers involved are all odd, even, or a mix: Beilock & DeCaro, 2007). In general, the more complex approaches enabled by GMA are more effective (Kanfer & Ackerman, 1989).

Second, those with higher GMA are better able to differentially focus their resource endowments because they are more capable of excluding extraneous information that often consumes the already limited resources of those with lower GMA (Gray, Chabris, & Braver, 2003). In fact, "the ability to focus attention on a central task and execute its required operations

¹ While fully recognizing that the choking framework and some of the related works cited are formulated around working memory capacity (WMC), in order to facilitate integration of this perspective within the broader literature linking mental ability with job performance, we reference general mental ability (GMA) in this manuscript. Even though there are some conceptual differences, GMA and WMC are highly related, and both function as a reliable proxy for assessing the cognitive or attentional resources that we discuss (Ackerman et al., 2005; Kane, Hambrick, & Conway, 2005; Randall, Oswald, & Beier, 2014).

while inhibiting irrelevant information" is a fundamental aspect of GMA (Beilock & Carr, 2005, p. 104). This ability has been demonstrated in multiple contexts, including the capacity to exclude distracting, superfluous conversation when attempting to engage with another task (the so-called cocktail party phenomenon where people differ in their ability to hear their name casually mentioned across a crowded, noisy room: Conway, Cowan, & Bunting, 2001). In addition, Kane and Engle (2003) found that GMA was positively associated with success rates in a Stroop task when trials were largely congruent (i.e., the color of the font and the color spelled by the letters matched) presumably because those higher (lower) on GMA were better (less) able to stay focused on the task. Further, in instances where trials were largely incongruent (i.e., the color of the font and the color spelled by the letters differed), GMA was positively associated with response speed, and these effects even carried over to the block of trials following the incongruent block (Hutchinson, 2011; Kane & Engle, 2003). In both instances, performance increases associated with GMA were attributed to an increased ability to keep cognitive resources focused on relevant aspects of the task over time.

Third, GMA tends to be positively related to the performance expectations that people hold for themselves. Because GMA tends to facilitate success across multiple life domains, individuals with higher (lower) levels of GMA come to expect corresponding levels of success in future endeavors (Judge, Jackson, Shaw, Scott, & Rich, 2007). In fact, "the success that intelligent individuals find in many areas of life should carry over to their self-concept" (Judge, Hurst, & Simon, 2009, p. 744). As a result, individuals with higher GMA tend to place a higher value on demonstrating their competence, which encourages them to strive for higher levels of performance than those with lower GMA (Kanfer, 1987). Moreover, GMA is positively related to individuals' propensity to take responsibility for their performance. Individuals with lower GMA are significantly more prone to blame their poor performance on external factors (e.g., bad luck) than individuals with higher GMA (Gimmig, Huguet, Caverni, & Cury, 2006), further indicating that higher GMA individuals broadly expect to perform well.

When GMA May Not Facilitate Performance

Despite the general value of GMA for performance, the choking framework laid out by Beilock and colleagues outlines conditions that tend to nullify these benefits. Choking does not afflict people or situations uniformly, and "the reason you choke depends on the characteristics of the task and on you yourself" (Beilock, 2010, p. 255). Choking is particularly prone to occur in situations characterized by high task complexity and high pressure to perform, or the felt "importance of performing well on a particular occasion" (Baumeister, 1984, p. 610). While numerous factors can influence pressure to perform (e.g., financial incentives, public scrutiny, etc.), goal type plays an important role (Sattizahn, Moser, & Beilock, 2016). For example, asking individuals simply to do their best when attempting a task can contribute to the creation of a relatively low pressure situation. In contrast, goals asking individuals to achieve a specific level of performance (e.g., a 20% increase in sales revenue, the publication of two high-impact articles each year) may increase felt pressure to perform (Beilock, Kulp, Holt, & Carr, 2004).

Felt pressure to perform meaningfully influences the strength of the relationship between GMA and performance on complex tasks (Beilock, 2008; Beilock & Carr, 2005; Beilock & DeCaro, 2007; Gimmig et al., 2006). In low pressure situations, GMA is generally positively related to performance as individuals with higher GMA out-perform those with lower GMA. However, when pressure is increased, performance generally becomes independent of GMA. In particular, those with lower GMA tend to be relatively unaffected by the additional pressure, while those with higher GMA choke and experience substantial performance decrements that nullify the GMA-performance relationship (Beilock, 2008; Beilock & Carr, 2005; Beilock & DeCaro, 2007; Gimmig et al., 2006).

Finally, we note that the choking framework has only been employed to advance our understanding of the relationship between GMA and task performance (i.e., performance in stable task environments), limiting our knowledge about when GMA facilitates performance more broadly. In particular, there are important differences in the level of complexity inherent in the stable environments relevant for task performance and the dynamic environments underlying

adaptive performance that raise the possibility that GMA may relate differently to performance in each (Lang & Bliese, 2009; LePine, 2005; LePine et al., 2000). We now turn our attention to advancing our theoretical understanding of how and when these underlying differences in complexity are most likely to affect the GMA-adaptive performance relationship.

Applicability to Adaptive Performance

Arising out of concerns that prevailing conceptualizations of performance were too static given the increasing dynamism of the work environment, adaptive performance was conceived to incorporate more dynamic task-centric behaviors (Hesketh & Neal, 1999; Pulakos et al., 2000). Originally conceptualized as a multifaceted concept, subsequent work has generally emphasized the "dealing with uncertainty" sub-dimension proposed by Pulakos et al. (2000). In fact, "the dimension of dealing with uncertain and unpredictable work situations is the only component of Pulakos et al.'s taxonomy that may well be distinct from task and citizenship performance" (Johnson, 2003, p. 91). In such a conceptualization, the task-centric behaviors individuals exhibit in response to complexity-inducing disruptions in the task environment is indicative of adaptive performance (Baard et al., 2014; Campbell, 1999; Dorsey et al., 2010; Griffin et al., 2007; Hesketh & Neal, 1999; Johnson, 2003; Jundt et al., 2015; LePine, 2005; Pulakos et al., 2000).

Further, while task and adaptive performance are both behavioral, task-focused phenomena, adaptive performance encompasses unlearning related to previously employed task-completion approaches as well as accordant relearning in the post-change context that fundamentally differentiate it from task performance (LePine et al., 2000). Consistent with this perspective, adaptive and task performance have long been considered conceptually distinct (Cortina & Luchman, 2013; Hesketh & Neal, 1999; Schmitt, Cortina, Ingerick, & Wiechmann, 2003). Accordingly, to further advance our understanding of this phenomenon, it is important that we differentiate adaptive and task performance empirically in a manner consistent with our conceptual distinction (LePine et al., 2000). Thus, when testing our theory we follow the lead of Lang and Bliese (2009) and employ discontinuous growth modeling to ensure that we appropriately evaluate adaptive performance separately from its task performance analog.

Further demonstrating the theoretical importance differentiating adaptive and task performance, the choking framework provides a coherent lens to understand the how the aforementioned differences in complexity between dynamic and stable environments are likely to impact the GMA-performance relationship. For example, in the stable contexts that characterize established notions of task performance, individuals largely rely on the execution of "habitual responses to familiar situations" (Weiss & Ilgen, 1985, p. 57). Because such ingrained responses don't place a high demand on cognitive resources, felt pressure to perform is unlikely to cause choking, and the framework predicts the typical positive relationship between GMA and task performance (Beilock & DeCaro, 2007; Beilock et al., 2004). In contrast, environments eliciting adaptive performance are associated with increased complexity (Dorsey et al., 2010; LePine, 2005) and necessitate unlearning and relearning that preclude reliance on routinized, habitual responses (LePine et al., 2000). Because equivalently complex and dynamic task-completion approaches are necessary to effectively counteract the aforementioned increase in uncertainty associated with environmental change (Ashby, 1956), a more nuanced relationship between GMA and adaptive performance is likely to emerge.

In such contexts, the relationship should be contingent on felt pressure to perform due in part to an increased prevalence of choking among those with higher GMA. The fact that individuals with higher GMA are more prone to choke than are those with lower GMA is an important consideration. If choking manifest equally across individuals regardless of GMA, one would still expect to see a performance advantage related to GMA, albeit at a uniformly lower level (i.e., a parallel shift of the GMA-performance curve). However, because the occurrence of choking is not uniform with respect to GMA, the slope of the GMA-performance relationship is reduced in situations conducive to choking (Beilock & Carr, 2005).

This asymmetrical performance decrement arises in part because the cognitive distraction brought about by pressure largely mitigates the GMA-driven advantages previously discussed (Beilock et al., 2004). Highlighting the central role that attention plays in choking (Sattizahn et al., 2016), felt pressure to perform overcomes the general ability of high GMA individuals to

devote their cognitive resources to the task at hand (Kanfer & Ackerman, 1989) by inciting intrusive thoughts, worries, and anxiety (DeCaro, Rotar, Kendra, & Beilock, 2010). In such situations, where high GMA individuals are unable to devote their full attention to the focal task, their performance declines to the level typically exhibited by those lower on GMA (Kane & Engle, 2000). Specifically, the resources required to deal with the pressure of the situation generally preclude high GMA individuals from executing the complex task-completion approaches that they are accustomed to relying on. This leads high GMA individuals to employ less efficacious and more resource-efficient associative approaches, resulting in more homogeneous performance (Beilock & Carr, 2005; Beilock & DeCaro, 2007).

While considerably less theoretical attention has been paid to those with lower GMA, multiple mechanisms may buffer these individuals from experiencing similar negative effects. First, they are particularly adept at identifying and utilizing simple, efficient task-completion approaches since this is their normal method of operation (Beilock & DeCaro, 2007). Further, the low cognitive resource requirements associated with these approaches enable them to be employed in the presence of felt pressure to perform (Beilock et al., 2004). Second, due to lower self-imposed performance expectations (Judge et al., 2007), a lower value placed on success (Kanfer, 1987), and a greater propensity to place blame for poor performance on external factors (Gimmig et al., 2006), lower GMA individuals may not feel pressure to perform to the same extent as those higher on GMA, reducing felt worry and anxiety. In fact, they may actually experience a useful increase in focus brought about by elevated performance expectations. In sum, to the extent that these effects collectively minimize GMA-driven differences in unlearning and relearning following an environmental change, the relationship between GMA and adaptive performance is likely to be diminished when felt pressure to perform is elevated.

The Importance of Goal Attributes

As noted earlier, goal attributes play a substantial role in determining felt pressure to perform (Beilock et al., 2004; Sattizahn et al., 2016). In addition, because goals are widely used to direct individual activities in organizations (Locke & Latham, 2002), employees are likely to

be subject to the resultant pressure differences. Collectively, these qualities make goal attributes a particularly important consideration. Because goal attributes play an ancillary role in the theory underpinning the choking framework, we utilize the concise attribute typology laid out by goal theory (Locke & Latham, 1990, 2002) to enhance theoretical rigor and further develop our understanding in this area. As alluded to previously, goal theory identifies three overarching goal types. The first goal type, *performance* goals, requires a specific level of task performance to be achieved, increasing pressure to perform relative to other goal types (Wood & Locke, 1990). In contrast, *do-your-best* goals encourage individuals to do just that and lack an external reference for success (or failure). Finally, *learning* goals are formulated around the development of a specific number of approaches or strategies facilitating task completion.

Indeed, viewing goal type through the lens of the choking framework adds theoretical richness to LePine's (2005) initial assertion that the relationship between GMA and adaptive performance should be contingent on the attributes of the goal being pursued. In particular, by comparing performance goals, which formed the foundation of LePine's work, to the two other goal types delineated by goal theory (i.e., do-your-best and learning goals), our understanding of the theoretical mechanisms via which goal attributes are able to moderate the GMA-adaptive performance relationship is enhanced. As noted previously, the complexity of the task-completion approaches employed is likely to be particularly relevant for facilitating adaptive performance, and because it is likely to be jointly affected by both individual GMA and the type of goal being pursued, we develop moderating hypotheses in order to determine whether goal type represents a meaningful boundary condition for the GMA-adaptive performance relationship (Busse et al., 2017; Cortina & Folger, 1998). Because performance goals are ubiquitous in modern organizations (Latham & Locke, 2006; Locke & Latham, 2002), we investigate potential effects of different goal types relative to the de facto standard performance goal, beginning with a comparison of performance and do-your-best formulations followed by a discussion focused on how performance and learning goals differ.

Differentiating Performance and Do-Your-Best Goals

Broadly, performance goals establish uniformly high outcome expectations that subsequently direct cognitive resources toward their completion (Locke & Latham, 1990, 2002). In contrast, do-your-best goals invite the self-imposition of a "wide range of acceptable performance levels" due to the lack of a consistent external performance standard (Locke & Latham, 2002, p. 706). While this flexibility is generally detrimental for individual performance, goal theory acknowledges that do-your-best goals generally surpass performance goals in highly complex situations where the proper course of action is unknown (Latham & Locke, 2006). While this would seem to indicate that do-your-best goals would be universally superior for promoting adaptive performance, we draw on the choking framework to explain why the most efficacious goal type is actually likely to be dependent on GMA.

In particular, Wood and Locke (1990) note that performance goals are likely to induce felt pressure to perform due to a perceived need to immediately achieve a difficult level of performance. When the means of achieving success are unknown, which is particularly likely to be the case in situations relating to adaptive performance as they require unlearning and relearning following a change (LePine et al., 2000), pressure to perform is likely to be especially pronounced (Locke & Latham, 2002). This pressure hinders the validation of potential task-completion approaches, leading people to adopt simple approaches (Latham & Locke, 2006; Wood & Locke, 1990). While this aligns with the approaches inherently preferred by those lower on GMA (Beilock & DeCaro, 2007), blunting potential negative effects, it is likely to represent a substantial change relative to the complex, systematic approaches generally utilized by those higher on GMA. Furthermore, because situations necessitating adaptive performance generally exhibit increased complexity relative to those associated with task performance (Baard et al., 2014; Dorsey et al., 2010; LePine et al., 2000), complex task-completion approaches are likely to be particularly efficacious for facilitating adaptive performance (Ashby, 1956; Beilock & DeCaro, 2007). By forcing individuals higher on GMA to adopt less effective, simpler task-completion approaches, performance goals increase their likelihood of choking.

Conversely, the external inducement to sustain performance at a high level provided by performance goals is likely to enhance the efficacy of the adaptive performance exhibited by individuals with lower GMA because they lack the inherent tendency to self-impose and maintain high performance expectations compared to those with higher GMA (Beilock, 2010; Kanfer & Ackerman, 1989). In other words, performance goals tend to homogenize post-change outcome expectations across individuals at a level closer to that generally exhibited by those with higher GMA. Because individuals with lower GMA have an innate difficulty concentrating on the focal task (Beilock & Carr, 2005; Kane & Engle, 2003), imposing elevated outcome expectations that increase focus on task completion (Locke & Latham, 1990, 2002) can help counteract the disruption in routine brought about by an environmental change. By enhancing resource availability, increased focus is likely to bolster unlearning and relearning in the post-change environment, elevating the adaptive performance of those lower on GMA accordingly.

In contrast, the flexibility inherent in do-your-best goals allows GMA-driven differences in performance expectations and cognitive resource allocation decisions (Sattizahn et al., 2016) to persist. In particular, because the tendency to internalize high self-imposed performance expectations and accept personal responsibility for poor performance are positively related to GMA (Gimmig et al., 2006; Judge et al., 2009), those with higher GMA are likely to innately desire high levels of performance following a change, encouraging them to focus on the required unlearning and relearning activities (LePine et al., 2000). In contrast, absent the rigidity imposed by performance goals, do-your-best goals allow individuals with lower GMA to follow their predisposition to blame post-change performance decrements on the external environment and lower their self-imposed performance expectations accordingly. Because reduced expectations generally diminish the cognitive resources devoted to completing the focal task (Locke & Latham, 1990, 2002), the ability of those lower on GMA to successfully accomplish the requisite unlearning and relearning following a change is likely to be diminished by do-your-best goals.

Thus, performance goals are likely to damp the relationship between GMA and adaptive performance by simultaneously mitigating the ability of individuals higher on GMA to adopt the

more complex (and effective) task-completion approaches that they prefer while also enhancing the task focus and adaptive performance of those lower on GMA. In contrast, the reduced pressure to perform associated with do-your-best goals (Latham & Locke, 2006; Wood & Locke, 1990) frees individuals to devote available cognitive resources to the focal task according to their own dispositions. Because choking is unlikely to occur under these circumstances, those with higher (lower) GMA are likely to out- (under-) perform those with lower (higher) GMA (Beilock & Carr, 2005). As such, compared to performance goals, do-your-best goals enable GMA-driven differences in task-completion approaches to manifest, strengthening (Gardner, Harris, Li, Kirkman, & Mathieu, 2017) the GMA-adaptive performance relationship.

Hypothesis 1: Goal condition will moderate the relationship between GMA and adaptive performance such that the relationship will be more positive in the presence of a do-your-best goal compared to a performance goal.

Differentiating Performance and Learning Goals

Another alternative to the imposition of a performance goal is the establishment of a learning goal, which specifies a set quantity of task-completion approaches to be developed rather than a particular level of task performance to be attained. As such, learning goals generally encourage the identification of more approaches than performance goals and are offered as a more viable alternative to performance goals for enhancing performance in complex situations (Locke & Latham, 2002). However, we draw on the choking framework to explain why GMA may influence the validity of this recommendation in the context of adaptive performance.

Broadly, GMA-driven differences in the complexity of the task-completion approaches employed are likely to persist to a greater extent with learning goals than with performance goals. Because learning goals aim to increase the number of approaches employed rather than change their content, those with higher GMA will exhibit greater aptitude and propensity for developing and employing more complex approaches (Beilock & Carr, 2005; Beilock & DeCaro, 2007; Kanfer & Ackerman, 1989). Further, employing a greater number of these complex task-

completion approaches is likely to enhance adaptive performance by increasing the depth and breadth of information integrated (Ricks, Turley-Ames, & Wiley, 2007), more fully capturing the complexity of the situation (Ashby, 1956; Beilock & DeCaro, 2007). In contrast, the simple associative approaches preferred by those with lower GMA tend to be most useful in correspondingly simple task environments, and when they are employed in complex situations (like those necessitating adaptive performance), they are likely to lead to erroneous conclusions (Beilock & DeCaro, 2007). Due to the relative inaccuracy inherent in any given associative approach, increasing the number of such approaches is likely to lead to confusing and conflicting indications.

In addition, because learning goals induce a broader focus with an emphasis on exploration rather than execution (Locke & Latham, 2002), they encourage adoption of new task-completion approaches. This malleability is likely to be particularly relevant for adaptive performance because the task-completion approaches previously utilized may not be optimal after the task environment changes (LePine, 2005; LePine et al., 2000). Moreover, those with higher GMA are likely to disproportionately benefit from this encouragement. Owing in part to their ability to exclude information deemed extraneous (Gray et al., 2003; Hutchinson, 2011; Kane & Engle, 2003), an achievement focus can constrain the thinking of those with higher GMA as "people's ability to think about information in new and unusual ways can actually be hampered when they wield too much brainpower" (Beilock, 2010, p. 66). Of particular relevance for unlearning and relearning, this focus makes those with higher GMA more loathe to abandon previously successful task-completion approaches than those with lower GMA (Beilock & DeCaro, 2007; Ricks et al., 2007). Thus, even though GMA facilitates the initial development of more complex task-completion approaches, it may also hinder unlearning and relearning by reducing the propensity to evolve after a change. By broadening the focus of attention, learning goals are likely to counter this tendency and enhance the adaptive performance of those higher on GMA.

Conversely, because individuals with lower GMA are less capable of differentially focusing their attention on a subset of available inputs (Gray et al., 2003), they are more likely to notice that their current approach is suboptimal, which helps foster adjustment in stable contexts (Ricks et al., 2007). Therefore, in contrast to those higher on GMA, the additional external inducement to explore (rather than execute) provided by learning goals is not likely to be particularly performance-enhancing. In fact, by shifting cognitive focus toward exploration and "away from task outcome achievement" (Winters & Latham, 1996, p. 237) learning goals encourage a more diffuse application of available cognitive resources compared to performance goals. Given that those with lower GMA don't innately value achievement to the same extent as those with higher GMA (Gimmig et al., 2006; Judge et al., 2009), they are more likely to devote their already limited cognitive resources toward the identification and maintenance of numerous task-completion approaches, rather than remaining focused on successfully completing the focal task (Locke & Latham, 1990, 2002). Moreover, because the task-completion approaches they utilize are often ineffectual given the heightened complexity associated with environmental dynamism (Beilock & DeCaro, 2007), the resultant unlearning and relearning of those lower on GMA is likely to be impeded, hampering the efficacy of their adaptive performance. In sum, compared to the relative homogeneity brought about by performance goals, learning goals encourage the manifestation of inherent GMA-driven differences, strengthening the GMA-adaptive performance relationship.

Hypothesis 2: Goal condition will moderate the relationship between GMA and adaptive performance such that the relationship will be more positive in the presence of a learning goal compared to a performance goal.

Method

Characterization of Adaptive Performance

In light of the growing importance of having employees deal successfully with changes in the workplace (Campbell, 1999; Hesketh & Neal, 1999), adaptive performance has been

proposed as a unique performance dimension with unique antecedents (Hesketh & Neal, 1999; Jundt et al., 2015; Schmitt et al., 2003). Consistent with this notion as well as other work in this domain (e.g., Carpini, Parker, & Griffin, 2017; Niessen & Jimmieson, 2016), we evaluated adaptive performance using the task-change paradigm, wherein an unexpected and unannounced change to the task environment is incorporated into the focal exercise (e.g., Drach-Zahavy & Erez, 2002; LePine et al., 2000). Such a change captures the essence of adaptive performance as it requires "taking action when necessary without having all the facts at hand; adjusting plans, actions, or priorities to deal with changing situations; and imposing structure to provide focus in dynamic situations" (Johnson, 2003, p. 91). The task-change paradigm appropriately emphasizes both the change-response nature of adaptive performance as well as its uniqueness relative to task performance (Baard et al., 2014; Jundt et al., 2015; Niessen & Jimmieson, 2016). As noted by LePine and colleagues (2000), this is a substantial improvement on the muddled operationalizations of adaptive performance that characterized early work in this domain.

Insert Figure 1 about here

In order to develop an appropriate and robust empirical framework in which to test our hypotheses, we follow Lang and Bliese (2009) and empirically differentiate multiple aspects of both task and adaptive performance. In this approach, *basal performance* connotes the initial level of task (i.e., pre-change) performance that an individual exhibits while *skill acquisition* indexes the rate at which task performance changes over time. Assuming a linear relationship to aid interpretability, these two parameters can be thought of as the intercept and slope, respectively, of a line depicting performance over time. Similarly, adaptive (i.e., post-change) performance is comprised of two corresponding aspects, transition and reacquisition adaptation, that represent predicted changes in the intercept and slope of the performance trajectory, respectively. *Transition adaption* captures temporally proximal performance shifts following a change and is enhanced by timely *recognition* and rapid responsiveness. In contrast,

reacquisition adaptation considers the rate at which performance evolves over time, emphasizing the long-term effects of the *recovery* efforts in the post-change context.

Further, to provide needed theoretical depth to our understanding of the nature of the relationship between GMA and adaptive performance over time (Beier & Oswald, 2012), we consider how people respond to multiple changes. Specifically, we note that it's well established that the response of an individual may evolve when exposed to a previously novel stimulus multiple times (Ackerman, 1988). Likewise, it would seem reasonable to expect people to perform differently when repeatedly faced with change-induced complexity, even if the nature of the changes varies. Consequently, we investigate the extent to which our hypothesized relationships hold over time, connoting "initial" and "subsequent" as appropriate labels to characterize this recurrent adaptive performance. Specifically, *initial* transition and reacquisition adaptation capture adaptive performance after a novel change while *subsequent* transition and reacquisition adaptation denote adaptive performance following a second change.

In order to better convey the nature of these performance aspects, each is also depicted graphically in Figure 1 for a hypothetical set of parameter values chosen to enhance presentation clarity. For example, in accordance with our discussion above, a positive linear trend is used to characterize the change in performance over time in order to provide a more intuitive depiction of skill acquisition and reacquisition adaptation. To foreshadow, such linear effects form the basis of our results; though we do also account for an observed curvilinear effect characterized by a decreasing slope over time that is consistent with the notion of diminishing returns inherent in learning processes (Kanfer & Ackerman, 1989). In addition, given that performance typically declines immediately following a change, we chose to depict negative transition and reacquisition adaptation parameters. While the amount of reduction shown is constant across change events for simplicity, in actuality the magnitude of the initial and subsequent adaptation aspects can (and generally will) differ. For example, to the extent that an individual is able to learn from previous changes, subsequent performance declines would be expected to be smaller than those exhibited initially.

Performance Task

For this study, a stock market exercise was utilized as the focal task. This exercise asks individuals to estimate pricing for multiple stocks given potential indicators of firm value (i.e., Advertising, Market Share and Growth). In order to bound the scope of the exercise, participants were told that stock prices would have a mean of \$100 and could vary from \$5 to \$200. In addition, they were told that the potential firm value indicators were on an index scale such that higher numeric values indicated higher levels of the indicated attribute (e.g., market share) and that larger quantities of the indicators would not be detrimental to the stock price. Performance is indexed by the distance between the individual's estimate of the stock price and the correct price (determined by a regression equation that is unknown to the participants). Initially, participants know very little about how the indicators are related to the "correct" stock price, but after submitting each price estimate, they are provided with the correct price for the stock. This provides them the opportunity to ascertain the nature of the underlying relationships via the application of various task-completion approaches (e.g., intuition, linear algebra) in order to improve the accuracy of their price estimates and thus elevate their performance over time.

To facilitate this process, as shown in Figure 2, the software participants utilized to compete the exercise was configured so that the top portion of the screen displayed information for the current and the previous four decision trials. Specifically, the potential firm value indicators for each trial were provided, along with the correct stock price, the participant's estimate, and the difference between those two values for the previous trials. Participants had up to 20 seconds to complete each individual decision trial and were informed that late responses were not allowed. Following the lead of DeShon and Alexander (1996), this time was divided into two sections to encourage participants to engage with the task. The first five seconds of each trial were "read only" allowing them time to reflect on their previous performance. Potential firm value indicators and their performance over the last four trials were provided, but participants could not enter their estimate during this time. Participants then had up to an additional 15 seconds to enter their estimate for the current decision trial.

 Insert Figure 2 about here

Creation of the basic task proceeded in accordance with previous instantiations (e.g., DeShon & Alexander, 1996; Drach-Zahavy & Erez, 2002; Earley, Connolly, & Ekegren, 1989), and the "correct" price for each stock was determined by using a linear regression equation incorporating the three performance indicators along with an error term that accounted for a nominal 10% of the variance in stock price. In order to evaluate adaptive performance following two changes, as depicted in Figure 1, the exercise incorporated three equal length performance episodes (i.e., task performance, initial adaptive performance and subsequent adaptive performance), and a unique regression equation was employed to generate the correct stock price in each. Specifically, in the pre-change, task performance episode, the regression equation used to calculate the deterministic portion of the correct stock price took the form: $Y_1 = 0X_1 + .7X_2 + .3X_3$, where X_1 denotes advertising, X_2 denotes market share and X_3 denotes growth. To demarcate the first change, the governing equation was changed to: $Y_2 = .15X_1 + .15X_2 + .7X_3$. For the second change, the equation shifted to: $Y_3 = .33X_1 + .33X_2 + .33X_3$. These changes were transparent as they were automatically and seamlessly integrated into the software used for the exercise. In this manner, we captured task performance in the pre-change episode along with adaptive performance following two distinct, unannounced changes. Further, as discussed below, the pattern of changes embodied in these equations was chosen to incorporate two key aspects of adaptive performance.

First, as previously discussed, adaptive performance requires unlearning and relearning (LePine et al., 2000), a notion incorporated into both change events. For the first change, participants had to unlearn approaches relying primarily on market share (as it went from being highly predictive in the pre-change episode to playing a relatively minor role after the change) and relearning relating to the increased importance of revenue growth in the post-change episode. The second change was intended to require unlearning of approaches that emphasized a subset of predictors and encourage relearning relating to the incorporation of all three predictors.

Second, changes necessitating adaptive performance typically increase the complexity of the task environment (Dorsey et al., 2010; LePine, 2005). To capture this phenomenon, we devised changes that increased the three task complexity aspects identified by Wood (1986). First, we introduced *dynamic complexity* by employing a unique regression equation in each performance episode, changing the indicator-price causal linkages in each. In other words, we systematically varied the relationship between the potential indicators of firm value (i.e., inputs) and the correct stock price (i.e., output) over time. In addition, *component complexity* increased as the number of potential value indicators actually affecting the correct stock price was increased from two to three. Finally, even though the linkage between the inputs and output was consistently linear, *coordinative complexity* was affected by redistributing indicator validity (i.e., regression weights) more evenly across the three inputs. This increases complexity by reducing the relative dominance of any one indicator of firm value, raising information processing requirements.

Finally, each performance episode was divided into 6 measurement occasions each of which represents the average performance for 15 individual estimation trials². In other words, over the course of 90 minutes, each participant was presented with 270 individual decision trials, which were subsequently aggregated to 18 measurement occasions (using the average performance in each block of 15 individual estimation trials) to track performance over time. Blocking trials in such a manner helps reduce noise in the outcome metric and is commonly employed by researchers employing discontinuous growth modeling to detect performance changes over time (e.g., Lang & Bliese, 2009; Niessen & Jimmieson, 2016; Thoresen, Bradley, Bliese, & Thoresen, 2004) and in studies using the stock market task (e.g., DeShon & Alexander, 1996; Earley et al., 1989). Further, in order to mitigate any order effects, the individual estimation trials within each episode were presented to each participant in random order (DeShon & Alexander, 1996).

² While these aggregation decisions were made *a priori* and in consideration of extant research and methodological best practices, as pointed out by an anonymous reviewer, the specific aggregation choice remains in some sense arbitrary. In order to evaluate the robustness of our effects, we also considered two alternative aggregation schemes: one incorporating 15 measurement occasions (i.e., 5 per performance episode) and another incorporating 21 measurement occasions (i.e., 7 per performance episode). The results reported below replicate across alternatives with the exception that the effect for subsequent transition adaptation associated with hypothesis 1 is not statistically significant in the first alternative. The full results of this analysis are available from the first author upon request.

Participants

Participants were recruited and voluntarily agreed to participate as part of a larger data collection approved by Michigan State University's Institutional Review Board (IRB# X13-758e "Individual Differences and Performance"). Primarily upper level undergraduate business students (96% juniors and seniors) enrolled at a large Midwestern university, participants received course credit for participating. A total of 261 students participated in the exercise, approximately evenly distributed across the three goal types. The sample was 51% female and largely White (76%) and Asian (22%). The average age was 21 years.

Procedure

When signing up for the study, participants were directed to an online survey to collect informed consent and the GMA measure. This was provided at least a day prior to completing the focal exercise to increase temporal and contextual separation between the collection of the intelligence measure and the performance data. Then, at their assigned time, participants reported to a classroom equipped with several computers pre-configured to run custom software created to implement the stock market exercise as previously described. Before beginning, participants were briefed on the nature of the task, provided with an overview of each firm value indicator, and introduced to the software. Because the regression equations employed to determine the correct stock price across performance episodes represent systematic changes in market valuation drivers, each individual decision trial was purported to mark the passage of one week. As a result, the performance task spanned a hypothetical duration of just over 5 years. Even though no mention of potential change was made during the training, this timeframe was chosen to make shifts to underlying market valuation drivers (e.g., investor sentiment: Baker & Wurgler, 2007) more plausible. Finally, the importance of each trial in the task was emphasized, and the participants' goal was specified. Participants then completed 6 practice trials in order to gain first-hand experience with the focal task and software. After answering any questions and reinforcing their goal for the session, participants began working on the focal task.

Measures

General Mental Ability was assessed using the Wonderlic Personnel Test – Quicktest (WPT-Q). This is a timed online test, and respondents have eight minutes to answer a battery of 30 questions. This test was developed to mirror the results that would be obtained using the Wonderlic Personnel Test (Wonderlic, 2004), which has been successfully used in a wide variety of field and lab contexts and generally demonstrates a high level of internal reliability (LePine et al., 2000). In order to increase interpretability, this measure was centered in the focal analysis.

Goal type was manipulated during the training administered to participants and reinforced in the software employed to implement the stock market exercise. Each session of participants was randomly assigned to one of the goal types prior to arriving in the laboratory. Consistent with the tenets of a specific and difficult performance goal laid out in goal theory (Locke & Latham, 1990) and in keeping with previous operationalizations for studies employing a stock market exercise (e.g., DeShon & Alexander, 1996), participants in the performance goal condition were given a specific, numeric performance goal for each trial. In particular, participants in this condition were told that successful performance was defined as estimating a stock price within \$7, and that as a result, their goal was to achieve this level of accuracy on each decision trial. Based on the results of a pilot study using a sample drawn from the same population as the intended participants³, the value of +/- \$7 was chosen to keep our operationalization consistent with longstanding contentions that the level of performance denoted by difficult goals should be unattainable for the vast majority (approximately 75% to 90%) of participants (e.g., Chesney & Locke, 1991; Winters & Latham, 1996; Wood & Bandura, 1989). Similarly, participants in the learning goal condition were assigned a specific, difficult learning goal that directed them to identify a specific number of approaches or strategies that facilitate

³ The results of a pilot study (n=28) in which participants were instructed to do their best when estimating the stock price for each trial indicated that this level of performance was attained on approximately 20% of the trials, consistent with the 75-90% failure rates previously used to operationalize a difficult performance goal.

performance. Specifically, participants were told to "identify and implement 7 effective strategies to maximize your performance", mirroring the verbiage used by Seijts, Latham, Tasa, and Latham (2004) to effectively impose a specific learning goal. The number of assigned approaches (i.e., 7) was chosen to represent a difficult goal level based on a review of past research operationalizing such learning goals in conjunction with the results of a pilot study. First, past research has generally found that requiring participants to identify between four and six performance enhancing approaches is an effective way to operationalize a learning goal (e.g., Seijts & Crim, 2009; Seijts et al., 2004; Winters & Latham, 1996). To help ensure that the learning goal was sufficiently difficult, the number of approaches incorporated was set somewhat higher than previous work in this domain because the present exercise had a dynamic component lacking in previous tasks. In addition, the results of a pilot study revealed that the number of approaches generally employed fell well short of the assigned value⁴. Finally, participants in the do-your-best condition were instructed to simply "do their best" on each trial.

Performance was indexed by the deviation between the "correct" and participant estimated stock prices for each trial. Specifically, the absolute value of the difference between the correct (e.g., 100) and user estimated (e.g., 75) stock prices was calculated for each trial (e.g., $|100-75| = 25$). Then, in order to increase interpretability (e.g., Drach-Zahavy & Erez, 2002), this raw performance metric was subtracted from 200 (e.g., $200 - 25 = 175$). This transformation simply inverts the direction of the performance metric so that better performance is indexed by higher values. Finally, this transformed value was averaged across each block of 15 estimation trials to construct the outcome variable for each of the 18 measurement occasions.

Time parameterization is a critical aspect of discontinuous growth modeling (Bliese & Lang, 2016). To adequately capture the specified aspects of task and adaptive performance, eight level-1 (i.e., within person) time variables were used to parameterize participant trajectories

⁴A pilot study (n=28) was conducted to gauge the breadth of task-completion approach utilization. After completing the stock market exercise, participants were presented with 12 blanks and asked to list any strategies they used to enhance performance during the task. The mean number of approaches reported was two. The maximum number of approaches reported was four and 75% of participants reported three or fewer.

across the 18 measurement occasions that comprised the three performance episodes. In order to effectively evaluate recurrent adaptive performance, we utilized a mixed coding scheme as codified by Bliese and Lang (2016). Consistent with the need to differentiate adaptive from initial performance (LePine et al., 2000), we utilized *relative* coding for both the transition and reacquisition parameters (Lang & Bliese, 2009; Niessen & Jimmieson, 2016). To avoid inadvisable and unwarranted extrapolation (Bliese & Lang, 2016; Pinheiro & Bates, 2000), we employed *absolute* coding for the non-linear (i.e., squared) time parameters used to capture curvature in the rate of skill acquisition and reacquisition. Using this parameterization (as shown in Table 1), the focal analysis evaluates transition adaptation by directly estimating the shift in intercept coinciding with each change relative to the initial level of performance exhibited (i.e., basal task performance). Reacquisition adaptation is directly evaluated by estimating the extent to which the slope in each post-change episode differs from the rate of skill acquisition.

Insert Table 1 about here

Results

All analyses were conducted in R (R Core Team, 2016) with multilevel modeling performed using the nlme library (Pinheiro, Bates, DebRoy, Sarkar, & the R Development Core Team, 2016). We began our analysis by evaluating the effectiveness of the goal condition manipulations. In order to capture deviations from the assigned goal condition, we followed Kozlowski et al. (2001) and asked participants to report on their engagement with the goal after completion of the focal task. To evaluate the functionality of the performance goal manipulation, participants were asked to report their adopted accuracy goal for each pricing task. The efficacy of the learning goal manipulation was evaluated by counting the performance enhancing approaches that participants reported finding useful. As shown in Table 2, the mean goal participants in the performance goal condition reported adopting (\$8.51) was close to the assigned value of \$7 and was significantly lower than that reported in either the do-your-best or

learning goal conditions. Further, the latter two conditions did not differ significantly from one another (\$18.05 and \$18.30, respectively). In addition, individuals in the learning goal condition listed an average of 6.06 approaches that they found useful, again approaching the assigned goal of 7 approaches. This value was significantly higher than the number reported in either the performance or do-your-best condition (2.44 and 2.45, respectively). Finally, in order to identify any systematic effort and persistence differences across conditions, post-task goal commitment was evaluated using five items from the scale proposed by Hollenbeck, Klein, O'leary, and Wright (1989), adapted to reflect the post-exercise nature of the assessment (Cronbach's alpha for the scale was .82). As shown in Table 2, there were no significant differences in the mean level of post-exercise goal commitment reported by those in the performance and the do-your-best (3.22 and 3.07, respectively) or learning goal (3.22 and 3.34, respectively) conditions. Collectively, these results speak to the effectiveness of the goal manipulations.

The means, standard deviations, and correlations for GMA, goal type, and performance in each episode are presented in Table 3. In order to evaluate the efficacy of our task and adaptive performance episodes, we compared the pattern of results with other recent studies in this domain (Drach-Zahavy & Erez, 2002; Lang & Bliese, 2009; Niessen & Jimmieson, 2016). We found that previous work has reported highly similar mean levels of performance across task and adaptive performance episodes. In addition, our inter-episode performance correlations are in-line with what has been presented previously as are the broader relationships among constructs with relevance to choking (e.g., GMA). In light of this support, we proceeded with our analysis.

 Insert Tables 2 & 3 about here

The proposed hypotheses were evaluated using discontinuous growth modeling (Singer & Willett, 2003) as it allows for the empirical differentiation of each aspect of task and adaptive performance (Lang & Bliese, 2009; Niessen & Jimmieson, 2016). Following Singer and Willett (2003), model specification began with an unconditional means model to evaluate the degree of

inter-individual variance. In this instance, the results indicate a viable degree of between individual variance ($ICC1 = .34$). Further model specification proceeded systematically as recommended by Bliese and Ployhart (2002) and Singer and Willett (2003). As such, linear time effects were initially specified, though further testing revealed non-linear (i.e., quadratic) effects consistent with a decreasing slope over time, which is typical for tasks involving learning (Kanfer & Ackerman, 1989; Lang & Bliese, 2009; Niessen & Jimmieson, 2016). As shown in Table 1, three quadratic time variables were added to the model to capture these effects.

Subsequent comparison of model deviance statistics indicated an improvement in model fit when each linear effect was individually allowed to vary randomly across individuals. Specifically, when compared to the fixed effect model, sequentially adding random effects for skill acquisition ($\chi^2(2) = 125.9, p < .001$), initial transition adaptation ($\chi^2(3) = 217.6, p < .001$), initial reacquisition adaptation ($\chi^2(4) = 41.2, p < .001$), subsequent transition adaptation ($\chi^2(5) = 30.1, p < .001$), and subsequent reacquisition adaptation ($\chi^2(6) = 48.9, p < .001$) all significantly improved model fit. Because of the low power of the random effect tests and *a priori* theoretical reasons, we included cross-level interactions for the quadratic time effects paralleling the focal linear effects in the final model as well (Snijders & Bosker, 1999). Finally, two additional model-specification steps were taken to appropriately account for the structure of the intra-individual errors. Specifically, we included a first-order autoregressive term ($\phi = 0.047$), and an exponential function of the time variable (estimated exponent = -0.012) was added to avoid estimation inaccuracy associated with error heteroscedasticity (Bliese & Ployhart, 2002). Both significantly improved model fit ($\chi^2(1) = 4.9, p < .05$ and $= 24.3, p < .001$, respectively).

 Insert Tables 4 & 5 about here

After completing the level-1 model specification outlined above, the substantive model was estimated, and each hypothesis was tested by evaluating the corresponding three-way cross-

level interaction terms. The results are presented in Table 4 and discussed below⁵. Hypothesis 1 stated that the relationship between GMA and adaptive performance would be stronger in the presence of a do-your-best goal compared to a performance goal. This effect corresponds to significant cross-level interactions between GMA (Level 2), do-your-best goal type (Level 2), and each of the four time variables parameterizing the specified aspects of adaptive performance (Level 1). While the estimated effects for initial adaptive performance were in the direction hypothesized, they did not reach statistical significance (for initial transition adaptation, $\gamma = 0.880$, $p = .07$ and for initial reacquisition adaptation, $\gamma = 0.283$, $p = .40$). Conversely, as predicted, the effects for both aspects of subsequent adaptive performance were positive and statistically different from zero (for subsequent transition adaptation, $\gamma = 3.900$, $p < .05$ and for subsequent reacquisition adaptation, $\gamma = 0.991$, $p < .01$). Thus, hypothesis 1 received mixed support. While the relationship between GMA and adaptive performance did not vary significantly between goal types after the initial change, it was significantly more positive in the presence of a do-your-best compared to a performance goal following the subsequent change.

Hypothesis 2 stated that the relationship between GMA and adaptive performance would be stronger in the presence of a learning goal compared to a performance goal. This effect corresponds to significant cross-level interactions between GMA (Level 2), learning goal type (Level 2), and each of the four time variables parameterizing adaptive performance (Level 1). With respect to initial adaptive performance, support is mixed. The relationship between GMA and initial transition adaptation did not vary significantly by goal condition ($\gamma = 0.392$, $p = .34$), but as predicted the relationship was significantly stronger for initial reacquisition adaptation ($\gamma = 0.668$, $p < .05$). Further, as predicted, the effects for both aspects of subsequent adaptive performance were positive and statistically different from zero (for subsequent transition adaptation, $\gamma = 3.776$, $p < .01$ and for subsequent reacquisition adaptation, $\gamma = 0.540$, $p < .05$).

⁵ Because there were no statistically significant relationships, either individually or jointly, between GMA or goal condition on the quadratic elements of adaptive performance, they are omitted from Table 4 for increased clarity. These additional parameters are available from the first author upon request.

Thus, hypothesis 2 also received mixed support, being supported for one of the two aspects of initial adaptive performance and both aspects of subsequent adaptive performance.

Table 5 presents the relationships relating GMA to each aspect of adaptive performance across goal conditions. The five relationships discussed above that differed from the analogous performance goal condition relationship are underlined. To further clarify the pattern of results, the significance of the simple effects (i.e., slopes depicted in Figures 3-6) is also noted. Consistent with our underlying theoretical arguments, the relationship between GMA and adaptive performance is generally positive in the do-your-best and learning goal conditions, with the coefficients relating GMA to three of the four adaptive performance aspects reaching statistical significance in each. Moreover, as expected, there were no significant relationships in the performance goal condition and the point estimates were an order of magnitude lower than those in the two other conditions, further supporting the existence of a meaningful boundary condition (Busse et al., 2017; Cortina & Folger, 1998). Lastly, we note that there were no significant differences between the do-your-best and learning goal conditions.

In addition, a comparison with Table 4 demonstrates that this pattern of relationships is quite different from those relating to task performance, proving empirical support for the uniqueness of task and adaptive performance. For example, the relationship between GMA and basal task performance was positive and significant in the performance goal condition; in contrast, GMA was not significantly related to either instance of transition adaptation in this goal condition. In addition, whereas the do-your-best and learning goal conditions largely facilitated a more positive relationship between GMA and both instances of reacquisition adaptation, with regard to the analogous skill acquisition aspect of task performance, both conditions were significantly detrimental compared to a performance goal.

To better illustrate the pattern of effects, interaction plots were also generated. Consistent with past work (e.g., Lang & Bliese, 2009; Niessen & Jimmieson, 2016) and due to a lack of significant quadratic effects, we again emphasize the linear effects for reacquisition adaptation in order to increase clarity and interpretability. Figure 3 visually presents the relationship between

GMA and initial transition adaptation by goal type. As noted above, even though the pattern is consistent with our hypotheses the slopes do not differ significantly across goal conditions. Figure 4 compares the relationship between GMA and initial reacquisition adaptation. As predicted by hypothesis 2, the relationship is more positive in the learning goal compared to the performance goal condition. Figure 5 and 6 provide the same information for subsequent transition and reacquisition adaptation, respectively. As predicted, the relationship between GMA and both aspects of subsequent adaptive performance is more positive in both the do-your-best and learning goal conditions than in the performance goal condition. Further, consistent with our theorizing, the relationship between GMA and adaptive performance is essentially flat in the performance goal condition because the performance of those lower on GMA is comparatively improved while that of those higher on GMA is somewhat diminished.

Insert Figures 3-6 about here

Discussion

Jundt et al. (2015, p. S67) recently called for additional consideration of "motivational factors, contextual influences, and the interactions between multiple factors as unique predictors of AP [Adaptive Performance]", and our results seem to highlight the utility of taking such an approach. First, by integrating the choking framework with goal theory, we identify goal type as an important contextual boundary condition for the GMA-adaptive performance relationship. In general, the relationship between GMA and adaptive performance tended to be more positive when participants were assigned a do-your-best or a learning goal compared to a performance goal, especially after the subsequent change. Compared to a performance goal, a goal of either of these types may facilitate more effective adaptive performance for those higher on GMA (compared to those lower on GMA) by reducing felt pressure to perform and encouraging more efficacious task-completion approaches. In contrast, the relationship is attenuated in the presence of a performance goal, making adaptive performance largely independent of GMA. This

provides an interesting caveat to the prevailing view that the positive relationship between GMA and performance is especially robust for complex tasks (Bell & Kozlowski, 2002; Schmidt et al., 2008). Moreover, moderation effects of this sort may help explain the conflicting evidence regarding the relationship between GMA and adaptive performance previously reported in the literature (e.g., Lang & Bliese, 2009; LePine et al., 2000). However, we note that while several point estimates in the performance goal condition were negative, we found only non-significant effects consistent with the choking framework and did not replicate the statistically significant negative effects for GMA previously reported. Nonetheless, the present study illustrates the theoretical importance of considering goal type for future adaptive performance work incorporating GMA.

It is also interesting to note the difference in the effects of goal type and GMA on task compared with adaptive performance. Adopting either a do-your-best or a learning goal significantly reduced the linear relationship between GMA and task performance (i.e., skill acquisition) compared with a performance goal. This stands in stark contrast to the aforementioned enhancing effects of do-your-best and learning goals for the analogous aspect of adaptive performance (i.e., reacquisition adaptation). Moreover, these results countermand the findings of Seijts and Crim (2009). Whereas they found that performance goals disproportionately benefitted those higher in GMA compared to learning goals when predicting *task performance*, our results demonstrate the opposite pattern for *adaptive performance*. That is, compared to either do-your-best or learning goals, performance goals seemed to hinder the adaptive performance of those higher on GMA (while bolstering those with lower levels of GMA). More broadly, our findings highlight the theoretical and practical importance of considering adaptive performance as a unique performance dimension with unique antecedents.

By extending the choking framework beyond the high-stakes testing situations where it has typically been applied (Beilock & Carr, 2005; Beilock et al., 2004; Sattizahn et al., 2016), we demonstrate its utility for enhancing our understanding of the relationship between GMA and performance. First, our results are consistent with the predicted increase in the potential for high

GMA individuals to choke when task complexity is high, as is apt to be the case when adaptive performance is required (Dorsey et al., 2010; LePine, 2005). Further, the increased pressure to perform inherent in performance goals seems to trigger this potential. Moreover, we expand the framework by considering learning goals, which have been conspicuously absent to this point.

Interestingly, we demonstrate that compared to other goal types, performance goals also have the ability to increase the adaptive performance of individuals with lower levels of GMA. This stands in contrast to previous work drawing on the choking framework that has found that those with lower levels of GMA were largely unaffected by pressure to perform (Beilock & Carr, 2005; Beilock et al., 2004). Because previous studies have manipulated goal type only in conjunction with other potential pressure-enhancing mechanisms (e.g., public scrutiny), the unique effects of goal type were obscured. By formalizing the role goals play in influencing felt pressure to perform and considering them independently from these other mechanisms, we contribute additional theoretical rigor to this framework. Beyond having a neutral to deleterious effect, we demonstrate that increased pressure to perform, in the form of a performance goal, may actually benefit the adaptive performance of certain individuals (i.e., those lower on GMA).

Our findings also raise a potential caution for organizations looking to maximize adaptive performance by employing multiple techniques shown to drive high levels of task performance. In particular, the present study highlights that the presumed positive effect of GMA may not be realized for adaptive performance if performance goals are also employed. Effects of this sort may contribute to understanding why even actively managed mutual funds that emphasize fund manager GMA are unable to deliver more net return to investors over time than simple index funds (Guercio & Reuter, 2014). While there are likely many factors in play, the longstanding and widespread use of performance based compensation structures for portfolio managers (Grinblatt & Titman, 1989) is likely to impose de-facto performance goals. As we demonstrate, these goals may hinder the ability of high GMA individuals to adapt compared to either do-your-best or learning goal formulations, especially over time. In turn, this effect may hinder long term

fund performance if underlying market fundamentals shift. More broadly, our findings present an opportunity to formally expand goal theory to better account for adaptive performance.

In addition, the present study begins to address recent concerns raised by Beier and Oswald (2012) noting a need to better understand how GMA influences performance over time. In particular, we demonstrate the importance of considering changes as part of an ongoing sequence rather than isolated occurrences. For example, the simple relationships between GMA and adaptive performance in both the do-your-best and learning goal conditions seemed more robust following the subsequent change compared to the initial change, indicating that the effects of individual differences may take time to fully materialize. By answering calls to take a more longitudinal approach to the study of adaptive performance (Baard et al., 2014), we demonstrate the potential for latent effects that take time to manifest and note that a study based on a single change (which has typified past research, though for an exception see: LePine et al., 2000) would have missed these delayed emergence effects.

Relatedly, support for the hypothesized effects was decidedly more robust after the subsequent change. In this case, those higher (lower) in GMA may be better (less) able to capitalize on their previous experiences when pursuing a do-your-best or learning goal due to the lower felt pressure to perform relative to a performance goal. Such findings add theoretical nuance to the choking framework which has emphasized repeated practice as a means of reducing the prevalence of choking and consequently improving performance in static situations (e.g., math problems: Beilock, 2010; Beilock et al., 2004). However, in dynamic organizational environments eliciting adaptive performance, this prescription may not be effective for higher GMA individuals pursuing a performance goal. Collectively, our results seem to support goal type as an important determinant of the extent to which individuals are able to effectively invest cognitive resources learning "how to adapt" over time (LePine et al., 2000, p. 573).

In particular, adaptive performance was maximized with high levels of GMA, a do-your-best or learning goal, and multiple changes to learn from. That is, those with higher levels of GMA seemed better able to capitalize on the opportunity when their inherent abilities were

paired with either a do-your-best or learning goal, and these effects appear to become stronger over time. This seems to imply that when the ability to learn is high, a performance goal may interfere with the realization of this potential. In contrast, the adaptive performance of those with lower levels of GMA was maximized with a performance goal. Given that these individuals may have relatively limited opportunities to learn (Kanfer & Ackerman, 1989), a performance goal may be effective in maximizing their potential by providing proximal motivation to focus their available cognitive resources. As pointed out by an anonymous reviewer, this pattern has substantial performance trajectory ramifications. Because the overall pattern of interactions between inherent mental ability and goal type was consistent across adaptive performance aspects and multiple changes, cumulative performance advantages (disadvantages) are likely to accrue for those individuals working toward a goal matched (mismatched) with their aptitude.

Limitations and Future Research

Based on our results, more fully explicating the nature of adaptive performance in response to repeated changes over time would seem like a fruitful avenue for future research. For example, by considering an even more extensive series of recurrent change events than the two analyzed here, a more complete and realistic picture of adaptive performance may emerge. In addition, work investigating the combinatory effects of multiple goal types (e.g., an initial learning goal followed by a performance goal) would seem like a natural extension of the current effort. Research considering how other individual differences (e.g., goal orientation: Dweck, 1986) impact adaptive performance over time would also be welcome. Because low motivation is not generally a precursor to choking (Beilock, 2010; Beilock, Schaeffer, & Rozek, 2017), the present study did not focus directly on motivational processes. Nonetheless, studies investigating the underlying motivation of individuals may deepen our understanding of this phenomenon.

In order to more fully realize the potential benefits of these approaches, we echo the concerns of Beier and Oswald (2012) and Jundt et al. (2015) and encourage researchers to also consider the continuity of the pre and post change tasks. In the present study, we retained the same fundamental task structure and manipulated the relative importance of each parameter to

introduce an unannounced change. As such, the consistency in performance across episodes (in terms of mean level and variance) does not point to any unwanted changes in the nature of the task across performance episodes, though we still encourage similar consideration in the future.

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Table 1
Level-1 Temporal Variables for Discontinuous Growth Models

	<i>Measurement Occasion (Trial)</i>																	
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
Variable	<i>(Task / Pre-Change)</i>						<i>(Initial Adaptive)</i>						<i>(Subsequent Adaptive)</i>					
Skill Acquisition (Time)	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
Initial Transition Adaptation	0	0	0	0	0	0	1	1	1	1	1	1	0	0	0	0	0	0
Initial Reacquisition Adaptation	0	0	0	0	0	0	0	1	2	3	4	5	0	0	0	0	0	0
Subsequent Transition Adaptation	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1
Subsequent Reacquisition Adaptation	0	0	0	0	0	0	0	0	0	0	0	0	0	1	2	3	4	5
Quadratic Skill Acquisition	0	1	4	9	16	25	25	25	25	25	25	25	25	25	25	25	25	25
Quadratic Initial Reacquisition Adaptation	0	0	0	0	0	0	0	1	4	9	16	25	0	0	0	0	0	0
Quadratic Subsequent Reacquisition Adaptation	0	0	0	0	0	0	0	0	0	0	0	0	0	1	4	9	16	25

Table 2

Manipulation Checks: Mean Post-Task Espoused Accuracy Objective, Task-completion Approach Count, and Goal Commitment by Goal Condition.

Goal Condition	Manipulation Check Mean Values		
	Per-trial accuracy	Approach count	Goal commitment
Performance (PG)	\$8.51	2.44	3.22
Do-your-best (DYB)	\$18.05	2.45	3.07
Learning (LG)	\$18.30	6.06	3.34
Mean difference (t)			
PG – DYB	–\$9.54 (6.49)***	–0.01 (0.03)	0.15 (1.20)
PG – LG	–\$9.79 (6.67)***	–3.62 (10.95)***	–0.12 (1.08)
DYB – LG	–\$0.25 (0.13)	–3.61 (11.74)***	–0.27 (2.35)*

Note. Espoused per-trial accuracy objective, task-completion approach count, and goal commitment were all collected after completion of the focal task. * $p < .05$. ** $p < .01$. *** $p < .001$.

Table 3
Between Individual Descriptive Statistics

Variable	M	SD	1	2	3	4	5
1. GMA	25.27	3.90	–				
2. Performance – pre-change	175.80	6.58	.21**	–			
3. Performance – post-change one	175.01	6.30	.23**	.50**	–		
4. Performance – post-change two	174.79	6.32	.29**	.55**	.54**	–	
5. Goal type contrast	0.49 / 0.52	0.50 / 0.50	.06 / -.12	.09 / .10	.09 / -.01	.11 / .04	–

Note. n = 261. Goal type contrast represents the comparison between a performance goal and a do-your-best or learning goal with results shown to the left and right of the slash, respectively. In both cases, the performance goal is coded 0 and the alternative goal type is coded 1. * $p < .05$. ** $p < .01$. *** $p < .001$.

Table 4

Discontinuous Growth Model Parameter Estimates of Goal Condition and GMA on Linear Aspects of Adaptive Performance

Fixed Effects	Estimate	SE	t
Level 1 parameters			
Intercept	171.868	0.955	180.025***
Skill acquisition (Time)	2.179	0.612	3.559***
Initial transition adaptation	-5.755	1.200	4.798***
Initial reacquisition adaptation	-0.470	0.827	0.569
Subsequent transition adaptation	-17.469	4.222	4.137***
Subsequent reacquisition adaptation	-2.316	0.807	2.872**
Quadratic skill acquisition	-0.268	0.114	2.346*
Quadratic initial reacquisition adaptation	-0.232	0.107	2.176*
Quadratic subsequent reacquisition adaptation	0.069	0.100	0.691
Level 2 and cross-level parameters			
GMA	0.506	0.245	2.065*
Do-your-best goal type (DYB)	0.269	1.380	0.195
Learning goal type (LG)	1.774	1.332	1.331
GMA × DYB	0.372	0.390	0.954
GMA × LG	0.444	0.325	1.366
Skill acquisition × GMA	0.011	0.157	0.069
Skill acquisition × DYB	0.973	0.885	1.100
Skill acquisition × LG	-0.257	0.855	0.301
Initial transition adaptation × GMA	0.070	0.308	0.229
Initial transition adaptation × DYB	-1.794	1.734	1.035
Initial transition adaptation × LG	-2.354	1.674	1.406
Initial reacquisition adaptation × GMA	-0.016	0.212	0.076
Initial reacquisition adaptation × DYB	-0.657	1.195	0.549
Initial reacquisition adaptation × LG	1.049	1.154	0.908
Subsequent transition adaptation × GMA	-0.132	1.084	0.122
Subsequent transition adaptation × DYB	-7.071	6.102	1.159
Subsequent transition adaptation × LG	0.109	5.893	0.019
Subsequent reacquisition adaptation × GMA	-0.062	0.207	0.299
Subsequent reacquisition adaptation × DYB	-0.714	1.165	0.612
Subsequent reacquisition adaptation × LG	0.942	1.126	0.836
Skill acquisition × GMA × DYB	-0.533	0.250	2.129*
Skill acquisition × GMA × LG	-0.483	0.209	2.318*
Initial transition adaptation × GMA × DYB	0.880	0.491	1.794
Initial transition adaptation × GMA × LG	0.392	0.409	0.958
Initial reacquisition adaptation × GMA × DYB	0.283	0.338	0.838
Initial reacquisition adaptation × GMA × LG	0.668	0.282	2.371*
Subsequent transition adaptation × GMA × DYB	3.900	1.726	2.259*
Subsequent transition adaptation × GMA × LG	3.776	1.438	2.626**
Subsequent reacquisition adaptation × GMA × DYB	0.991	0.330	3.007**
Subsequent reacquisition adaptation × GMA × LG	0.540	0.275	1.966*

Note. GMA is centered at the sample average to aid interpretability. $n = 261$. $k = 4695$. * $p < .05$.

** $p < .01$. *** $p < .001$.

Table 5

Estimates of the Linear Simple Effects Relating General Mental Ability and Adaptive Performance by Goal Condition.

Goal Type	Initial Adaptive		Subsequent Adaptive	
	Transition (Recognition)	Reacquisition (Recovery)	Transition (Recognition)	Reacquisition (Recovery)
Performance	0.070 (0.308)	-0.016 (0.212)	-0.132 (1.084)	-0.062 (0.207)
Do-your-best	0.950 (0.382)*	0.268 (0.263)	<u>3.767 (1.341)**</u>	<u>0.929 (0.256)***</u>
Learning	0.462 (0.269)	<u>0.651 (0.185)***</u>	<u>3.643 (0.944)***</u>	<u>0.478 (0.180)**</u>

Note. n = 261. k = 4695. For simple effects, * p < .05. ** p < .01. *** p < .001 Standard errors appear in parentheses. Underlining indicates that an estimated effect differs significantly (p < .05) from the corresponding performance goal condition parameter. .

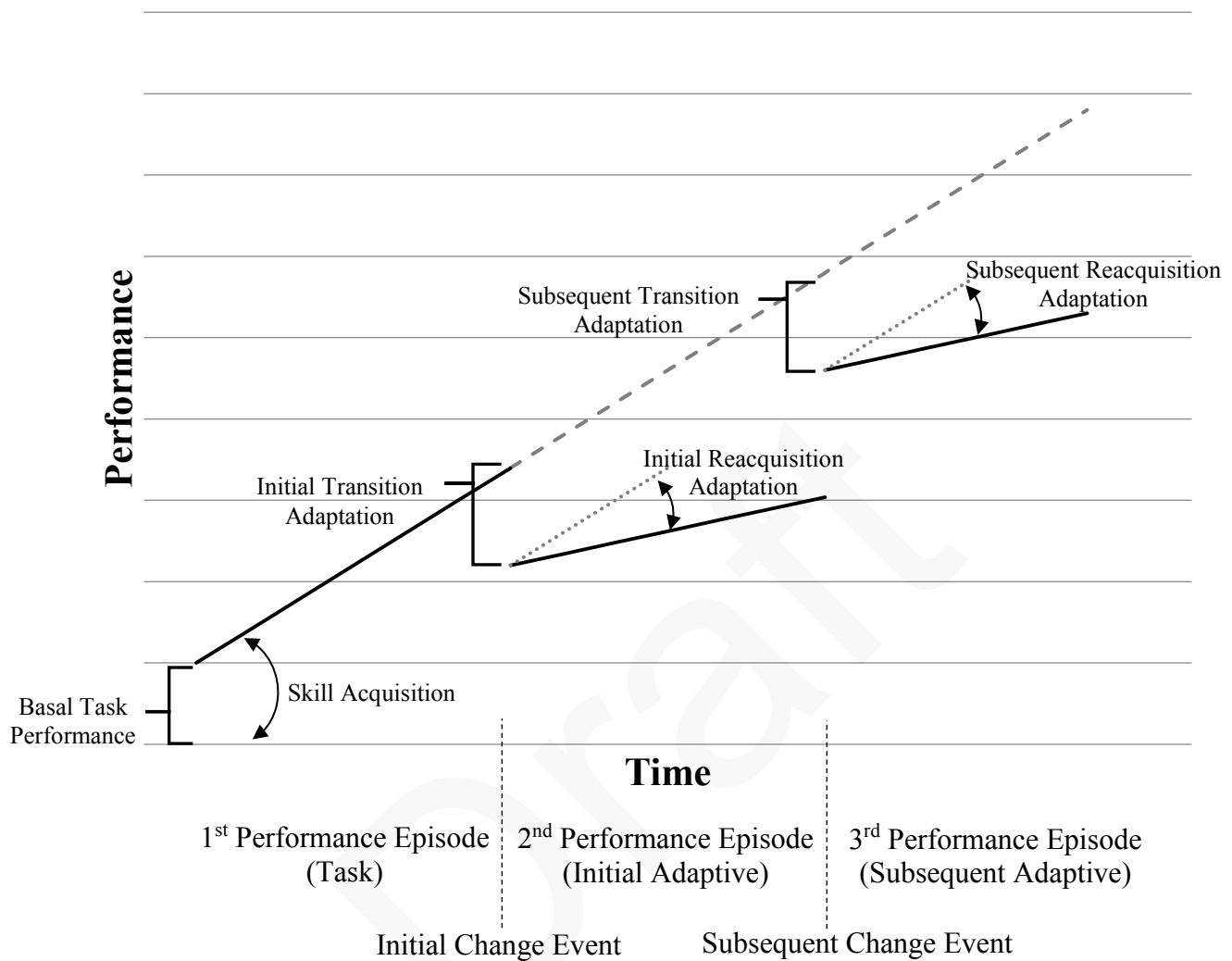


Figure 1. Stylistic illustration of level-1 discontinuous growth modeling parameters

Note. This is an extension of the model proposed by Lang & Bliese 2009. For ease of presentation and clarity, a linear model with hypothetical performance parameters of illustrative signs and magnitudes is depicted.

Summary of Past Performance (Last 4 weeks)					
	4 Weeks Ago (Week 1)	3 Weeks Ago (Week 2)	2 Weeks Ago (Week 3)	1 Week Ago (Week 4)	Current Week (Week 5)
Advertising	20	150	160	40	50
Market Share	130	130	60	150	30
Revenue Growth	130	30	80	50	150
Stock Price	\$120	\$119	\$78	\$138	\$?
Your Estimate	\$80	\$120	\$60	\$78	\$?
Difference	\$-40	\$1	\$-18	\$-60	\$?
Achieved Goal	NO	YES	NO	NO	
Remember, this task is an important determinant of your performance evaluation. Your goal is to be within +/- \$7 of the actual stock price for this week's estimate.					
Do not enter anything until prompted. Based on the performance information above, what is your estimated stock price for this organization? (5 s remaining): ■					

Figure 2. Screen capture of implemented stock market exercise for performance goal condition

Note. Goal-specific information varied by condition. In the do-your-best goal condition, the software told participants to "do your best when estimating the price of this week's stock". In the learning goal condition, the software instructed participants to "identify and implement 7 effective strategies to maximize your performance".

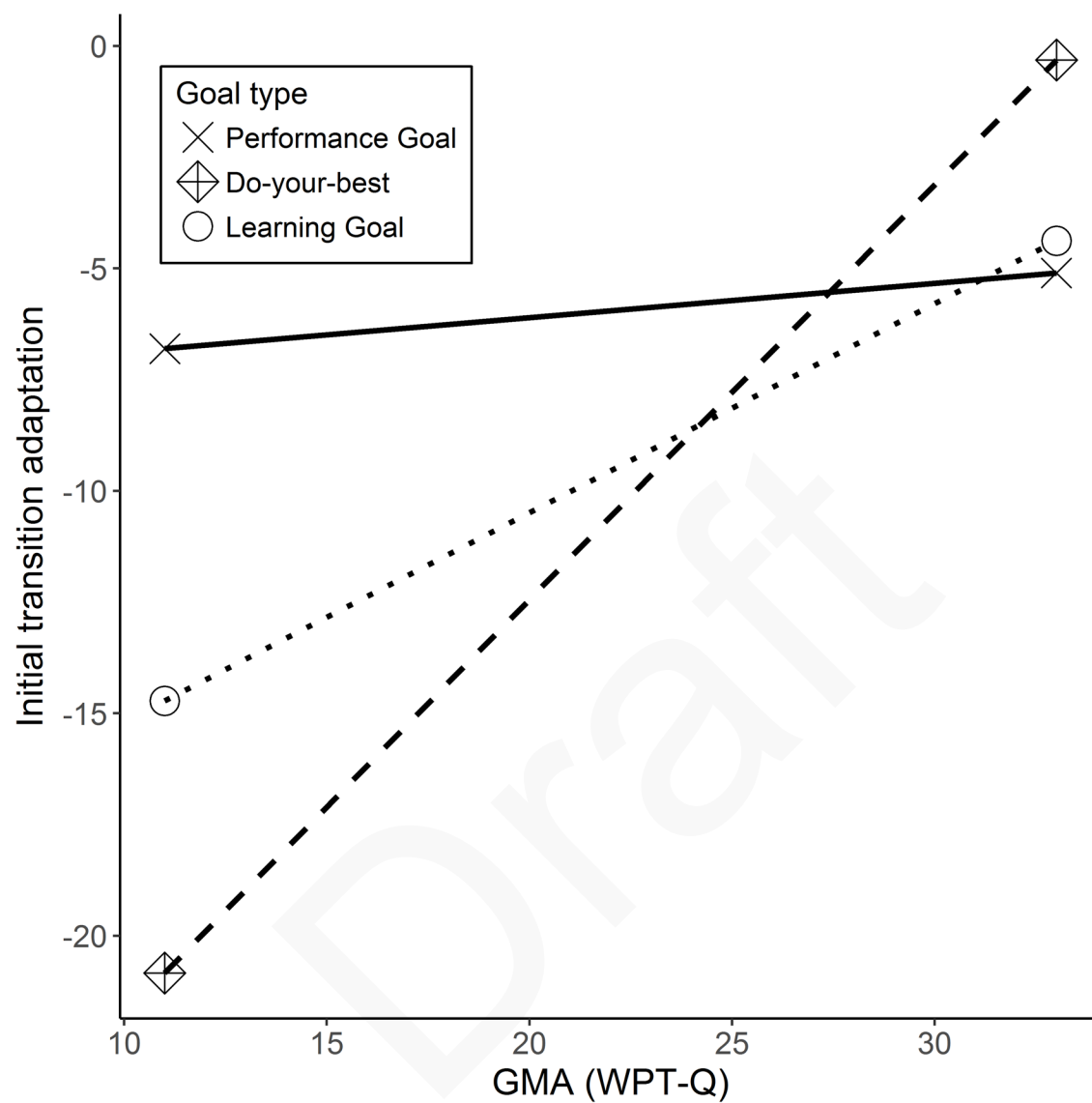


Figure 3. Comparison of the relationship between GMA and initial transition adaptation by goal type.

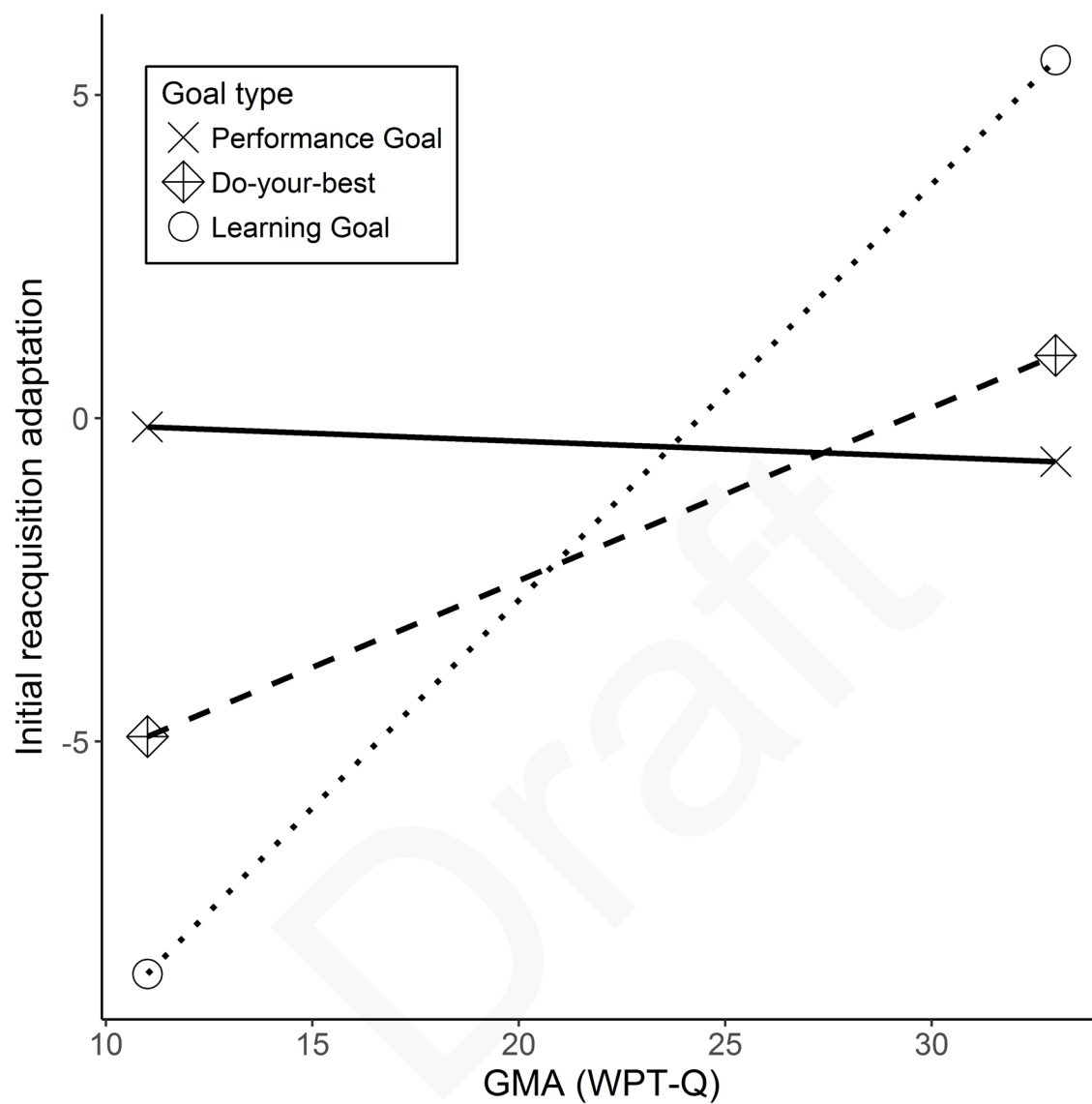


Figure 4. Comparison of the relationship between GMA and initial reacquisition adaptation by goal type.

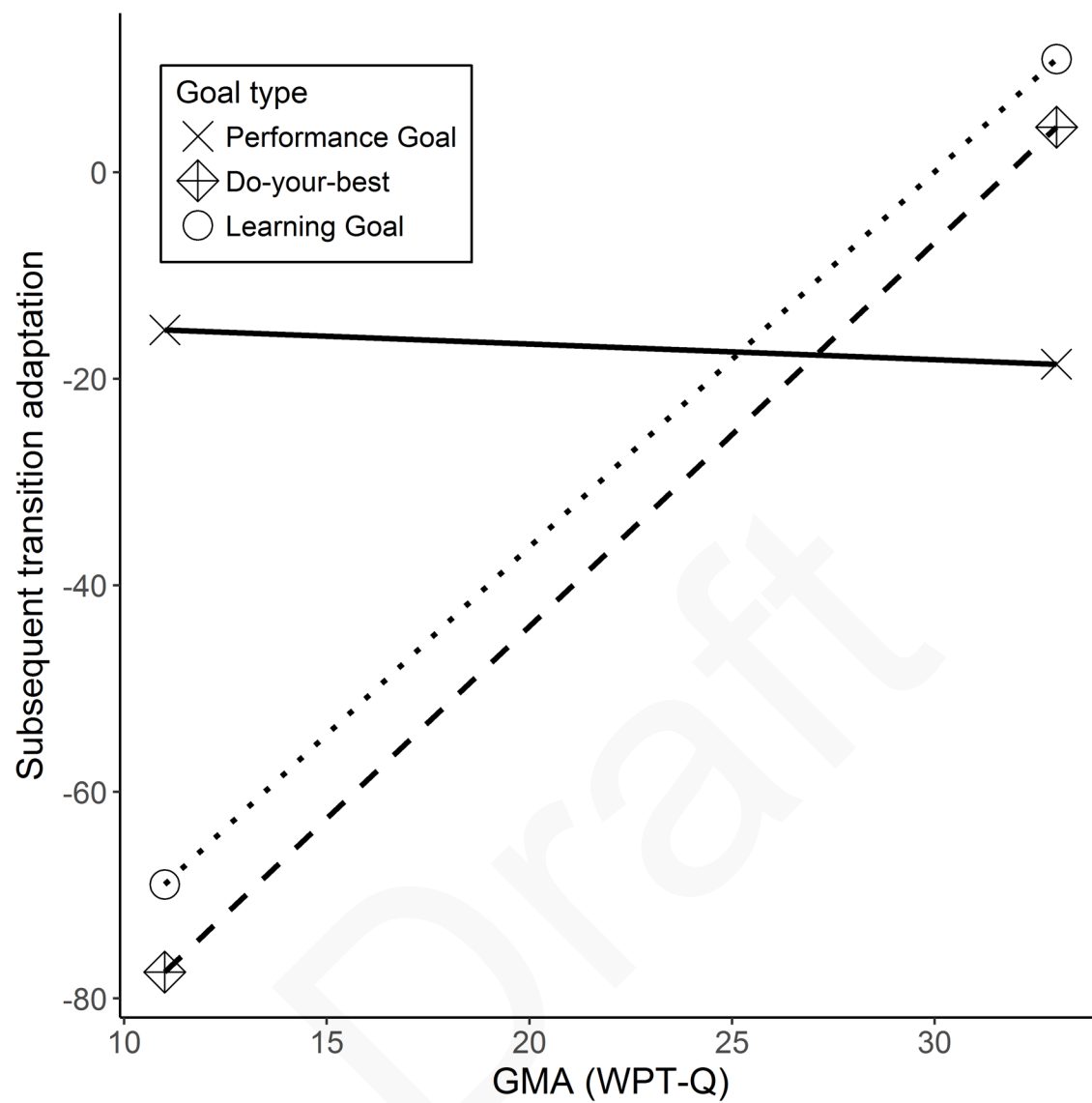


Figure 5. Comparison of the relationship between GMA and subsequent transition adaptation by goal type.

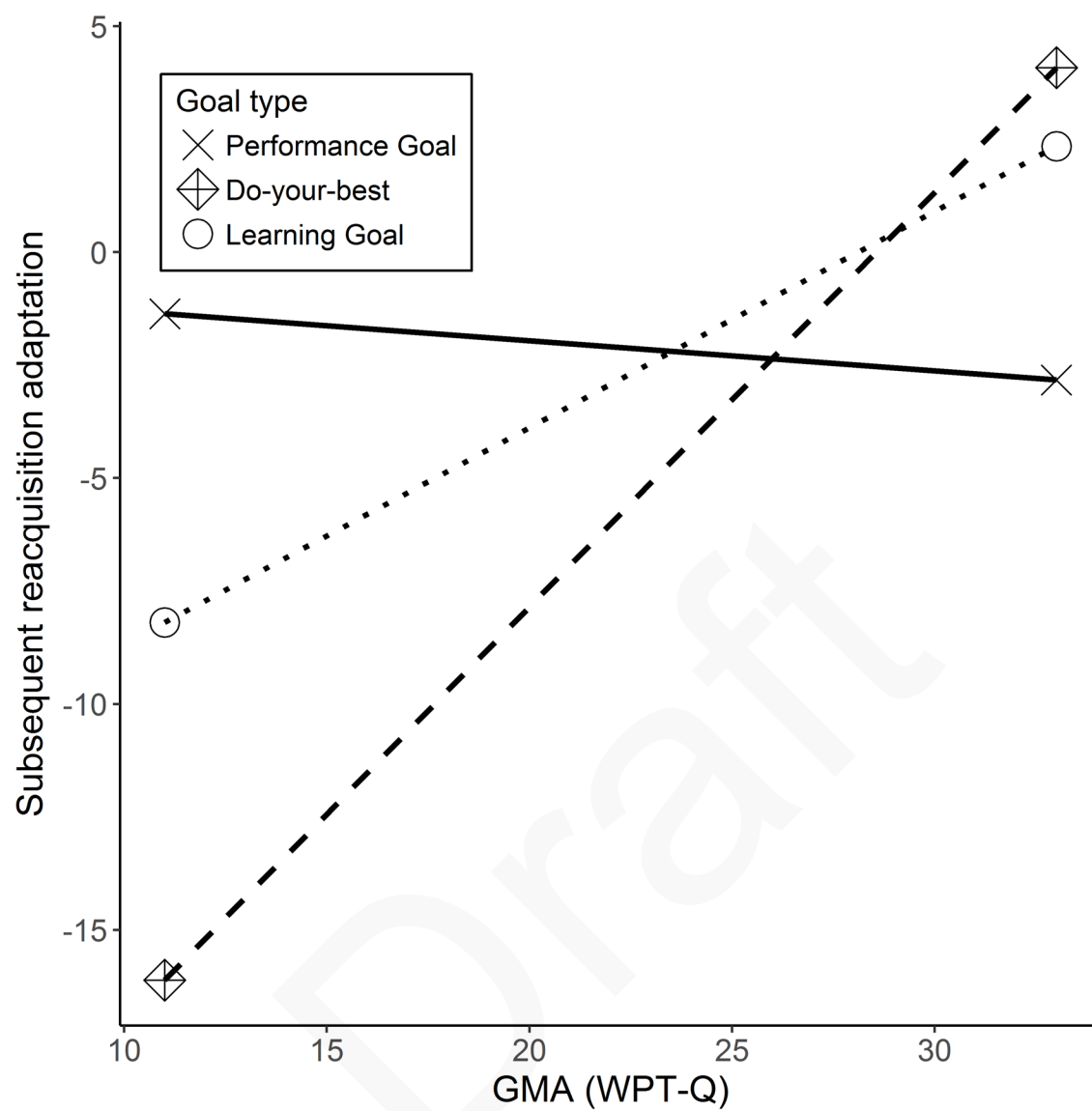


Figure 6. Comparison of the relationship between GMA and subsequent reacquisition adaptation by goal type.